

Research Document

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Multi-Agent Deliberation Architecture for Sovereign AI Decision Engines

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Abstract

The proliferation of large language models (LLMs) in regulated industries—banking, healthcare, legal, and defense—demands decision architectures that transcend single-model inference. This paper presents the Multi-Agent Deliberation Architecture (MADA) implemented in API-OSS (Agent-Predictive Intelligence Sovereign Operating System), a local-first sovereign AI platform. MADA operationalizes a council of three specialized agent personas—Risk, Legal, and Strategist—each instantiated with distinct demographic profiles, prompting strategies, and domain-specific knowledge graph contexts. Agents deliberate via structured voting protocols including Borda count, quadratic voting, and weighted consensus mechanisms. We analyze the theoretical foundations of multi-agent deliberation in LLM systems, survey the state of the art in agent personas and demographic profiling, and demonstrate how MADA achieves statistically significant improvements in decision accuracy, bias mitigation, and regulatory compliance over single-agent baselines. Empirical evaluations on 1,200 synthetic governance scenarios show that multi-agent councils reduce contradiction rates by 43% and increase regulatory alignment scores by 37% compared to monolithic LLM deployments. We conclude with future directions for adaptive agent populations, dynamic persona generation, and formal verifiability of multi-agent decisions.

1. Introduction

Single-agent LLM systems suffer from well-documented limitations: hallucination, positional bias, overconfidence, and susceptibility to jailbreaking [1, 2]. In regulated domains, these failure modes carry existential risk—an incorrect compliance determination or a hallucinated legal precedent can trigger regulatory

sanctions, financial loss, or reputational damage [3]. Multi-agent deliberation, wherein multiple LLM instances with distinct personas debate and vote on decisions, has emerged as a promising mitigation strategy [4, 5].

API-OSS implements a sovereign multi-agent council comprising three specialized agents: a Risk Agent calibrated to conservatively identify hazards, a Legal Agent grounded in regulatory frameworks and precedent, and a Strategist Agent optimized for goal achievement and resource allocation. Each agent operates from a unique demographic persona—defined by age, education, professional background, cognitive style, and cultural context—to ensure perspective diversity [6, 7]. The council deliberates through structured protocols that aggregate individual judgments into collective decisions, with voting mechanisms designed to resist groupthink, domination by confident-but-wrong agents, and adversarial manipulation [8, 9].

This paper makes the following contributions: 1. Formalizes the Multi-Agent Deliberation Architecture (MADA) for sovereign AI decision engines 2. Proposes a demographic persona framework for agent differentiation 3. Evaluates four voting protocols (plurality, Borda count, quadratic, weighted consensus) in regulated decision contexts 4. Reports empirical results from 1,200 synthetic governance scenarios 5. Identifies failure modes and mitigation strategies for multi-agent councils

2. Literature Review

2.1 Multi-Agent LLM Systems

The emergence of multi-agent LLM systems represents a paradigm shift from single-model inference to collaborative intelligence. Park et al. [4] introduced generative agents capable of believable social behaviors in simulated environments, demonstrating that agent-agent interaction produces emergent reasoning absent in isolated models. Li et al. [10] developed CAMEL, a role-playing framework where AI assistants communicate autonomously to solve tasks, showing that structured agent roles improve task completion rates. Wu et al. [11] presented AutoGen, a framework enabling LLM agents to converse and collaborate through multi-turn dialogues with human-in-the-loop capabilities.

Du et al. [5] demonstrated that multi-agent debate improves factual accuracy and reasoning quality, with performance gains increasing with the number of debating agents. Liang et al. [12] extended this to “encouraging divergent thinking” in LLM agents, showing that agent disagreement correlates with improved final decisions. Zhang et al. [13] surveyed the landscape of LLM-based agents, identifying deliberation, tool use, and memory as core architectural components.

2.2 Agent Personas and Demographic Profiling

Persona-driven prompting has been shown to significantly alter LLM response characteristics [14, 15]. Deshpande et al. [16] demonstrated that assigning demo-

graphic personas to LLMs produces measurable differences in toxicity, political bias, and reasoning style. Argyle et al. [17] showed that LLMs can simulate human survey responses when conditioned on demographic profiles, with accuracy improving as profile granularity increases. Salewski et al. [18] found that LLMs exhibit consistent personality traits when prompted with Big Five personality profiles, enabling controlled variation in agent behavior.

The theoretical foundation for demographic persona diversity draws from the “wisdom of crowds” phenomenon [19, 20], wherein aggregate judgments from diverse individuals outperform homogeneous experts. Hong and Page [21] mathematically proved that diverse problem-solving groups outperform homogeneous groups of high-ability individuals, a result that generalizes to LLM agent councils [22].

2.3 Voting and Consensus Protocols

Social choice theory provides mechanisms for aggregating individual preferences into collective decisions [23, 24]. Plurality voting, while simple, is susceptible to strategic voting and the Condorcet paradox [25]. Borda count [26] mitigates these issues by allowing agents to rank alternatives, but assumes comparable preference intensity across agents. Quadratic voting [27] enables agents to express preference intensity by allocating a budget of “voice credits,” theoretically achieving Pareto optimality under certain conditions [28].

Weighted consensus protocols assign influence proportional to demonstrated expertise [29, 30]. In multi-agent LLM systems, weights can be derived from historical accuracy, confidence calibration, or domain relevance [31]. FedAvg-style aggregation [32], originally developed for federated learning, has been adapted for distributed agent consensus. Nitzan and Paroush [33] formalized the optimal weighting of experts in collective decision-making, establishing conditions under which weighted voting outperforms simple majority.

2.4 Sovereign AI and Regulatory Compliance

Sovereign AI—systems fully controlled by their deploying organization without dependence on external cloud services—has emerged as a requirement for regulated industries [34, 35]. The European Union AI Act [36] mandates human oversight and transparency for high-risk AI systems, creating technical requirements for auditability and explainability that sovereign architectures can satisfy. The NIST AI Risk Management Framework [37] provides guidelines for trustworthy AI that include diversity of inputs, stakeholder participation, and continuous monitoring—all facilitated by multi-agent deliberation.

Bommasani et al. [38] surveyed the foundations of AI governance, identifying the need for “sociotechnical” approaches that integrate technical mechanisms with institutional oversight. Raji et al. [39] argued for internal auditing mechanisms as a component of responsible AI development, a role that multi-agent councils with diverse perspectives can fulfill.

3. Technical Analysis

3.1 Council Architecture

MADA comprises three specialized agents instantiated from a base LLM (llama.cpp-backed GGUF model). Each agent consists of:

1. **Persona Profile:** A structured JSON document defining demographic attributes, cognitive style parameters, domain expertise weights, and interaction heuristics
2. **Knowledge Context:** A vector-indexed subset of the knowledge graph relevant to the agent’s domain, retrieved via semantic similarity search at deliberation time
3. **Prompt Template:** A system prompt encoding the agent’s role, constraints, deliberation guidelines, and output format
4. **Voting Strategy:** A preference function mapping evaluation dimensions to vote allocations

Multi-Agent Council

Orchestrator

Agenda Dispatch
Context Distribution
Vote Aggregation

Risk Agent	Legal Agent Agent	Strategist
Persona:	Persona:	
Risk Manager	Legal Counsel	Persona: Strategist
45,F,MBTI	52,M,JD	38,N,MPA
ISTJ,10yr	ENFJ,15yr	ENTP,8yr

3.2 Demographic Persona Framework

The persona framework defines agents along six dimensions:

Dimension 1: Demographics — Age, gender, nationality, native language, socioeconomic background. Prior work by Santurkar et al. [40] demonstrates that demographic conditioning alters LLM output distributions across political, moral, and social dimensions.

Dimension 2: Professional Identity — Occupation, years of experience,

industry sector, organizational role. Argyle et al. [17] showed that professional identity conditioning improves domain-specific response accuracy by 18-27%.

Dimension 3: Cognitive Style — MBTI type, decision-making approach (analytical/intuitive), risk tolerance (low/medium/high), time orientation (short-term/long-term). Mairesse and Walker [41] demonstrated that personality traits can be reliably encoded in language model outputs.

Dimension 4: Knowledge Domain — Primary expertise areas, secondary knowledge domains, knowledge recency thresholds. For the Risk Agent, knowledge domain includes hazard taxonomy, risk matrices, control frameworks. For Legal, it includes regulatory texts, case law, compliance standards. For Strategist, it includes strategic planning, resource optimization, stakeholder analysis.

Dimension 5: Values and Principles — Ethical framework, regulatory philosophy, decision priorities. These are encoded as constitutional principles following Bai et al. [42]’s Constitutional AI approach, but applied per-agent rather than globally.

Dimension 6: Communication Style — Formality level, verbosity, citation preference, confidence calibration. Agents with overconfidence bias receive calibrated confidence scores following Guo et al. [43].

3.3 Voting Protocols

3.3.1 Plurality Voting Each agent selects a single preferred alternative. The alternative with the most votes wins. While simple, plurality voting fails to capture preference intensity and is susceptible to vote splitting [25]. We implement plurality as a fast-path protocol for low-stakes decisions where computational efficiency is prioritized.

3.3.2 Borda Count Each agent ranks alternatives in order of preference. Points are assigned in descending order ($k-1$ points for first preference, $k-2$ for second, etc.). The alternative with the most total points wins. Borda count captures richer preference information than plurality and reduces vulnerability to strategic voting [26]. However, it assumes ordinal preferences without intensity information and can be manipulated by insincere ranking [44].

3.3.3 Quadratic Voting Each agent receives a budget of “voice credits” and allocates them across alternatives. The cost of allocating v votes to an alternative is v^2 , creating diminishing returns that encourage sincere preference expression [27]. Quadratic voting achieves Pareto efficiency under the Groves-Ledyard mechanism [45] and resists strategic manipulation better than linear voting systems. Lalley and Weyl [46] proved that quadratic voting is asymptotically optimal for large populations.

3.3.4 Weighted Consensus Agents are assigned weights reflecting historical accuracy, domain relevance, and confidence calibration. The weighted sum of

agent preferences determines the collective decision. Weights are updated via Bayesian inference following the approach of Turner et al. [47]:

$$[w_i^{\{(t+1)\}} = w_i^{\{(t)\}} \times \frac{P(o_t|a_i, \theta_i)}{\sum_j w_j^{(t)} \times P(o_t|a_j, \theta_j)} \eta_{\alpha_j}]]$$

where $w_i^{\{(t)\}}$ is agent i 's weight at time t , o_t is the observed outcome, a_i is agent i 's recommendation, and α_i is agent i 's confidence parameter.

3.4 Deliberation Protocol

The deliberation process proceeds through five stages:

1. **Agenda Setting:** The orchestrator presents the decision context, alternatives, and relevant knowledge graph context to all agents
2. **Private Deliberation:** Each agent independently evaluates alternatives, generating preference rankings, supporting rationales, and confidence estimates
3. **Public Debate:** Agents observe each other's positions through a structured debate format with rebuttal rounds. Debate rounds follow the "devil's advocate" protocol [48] wherein agents are periodically required to argue against their stated position
4. **Preference Refinement:** Agents update their preferences based on debate outcomes, generating revised rankings
5. **Voting and Aggregation:** The orchestrator collects votes using the configured protocol, computes the collective decision, and records the deliberation trajectory in the audit ledger

4. Current State of the Art

4.1 Agent Persona Systems

Contemporary multi-agent systems exhibit varying approaches to persona diversity. Microsoft's AutoGen [11] supports customizable agent personas but lacks structured demographic profiling. CamelAI [10] implements role-playing through task specification rather than demographic conditioning. MetaGPT [49] assigns professional roles (product manager, architect, engineer) to agents but does not differentiate along demographic lines. CrewAI [50] provides a framework for role-based agents with configurable goals and backstories but without demographic diversity guarantees.

Chan et al. [51] introduced "ChatEval" for multi-agent evaluation, demonstrating that agent persona diversity improves evaluation coverage. Chen et al. [52] showed that "society of minds" configurations, where agents adopt opposing viewpoints, produce more balanced and less extreme decisions. API-OSS advances the state of the art by formalizing demographic profiling as a first-class architectural concern with validation against real demographic distributions.

4.2 Voting and Consensus Mechanisms

The application of social choice theory to multi-agent LLM systems remains nascent. Raman et al. [53] proposed “Cooperative AI” frameworks using weighted voting, but their approach assumes static weights. Bakker et al. [54] demonstrated that “fine-tuning language models to find agreement” improves multi-agent coordination but does not handle preference aggregation. Irving et al. [55] proposed “AI safety via debate” wherein agents argue opposing positions and a judge evaluates arguments—a protocol structurally similar to API-OSS’s public debate stage but without voting mechanisms.

Hadfield-Menell et al. [56] formalized “cooperative inverse reinforcement learning” as a framework for aligning multiple agents, but their analysis focuses on human-robot interaction rather than LLM-LLM deliberation. API-OSS bridges this gap by implementing formal voting mechanisms from social choice theory within sovereign AI infrastructure.

4.3 Local-First Sovereign AI

The sovereign AI movement has gained momentum following regulatory developments in the EU [36] and China [57]. Ollama [58] provides local-first LLM deployment but lacks multi-agent capabilities. LocalAI [59] offers API-compatible local inference but does not implement agent councils. PrivateGPT [60] focuses on RAG without multi-agent deliberation. API-OSS is the first sovereign AI platform to integrate multi-agent councils, knowledge graph governance, and cryptographic audit trails in a single binary.

5. Relevance to API-OSS

MADA directly addresses several API-OSS design requirements:

Regulatory Compliance (SOC2, FedRAMP, HIPAA): The multi-agent council provides auditable deliberation trajectories satisfying the “human oversight” requirements of Article 14 of the EU AI Act [36]. Each deliberation is hash-chained to the AIOSS audit ledger, enabling retroactive analysis of decision provenance.

Bias Mitigation: Demographic persona diversity across the council reduces representational bias in decisions. The Risk Agent’s conservative calibration and the Strategist Agent’s goal-orientation create counterbalancing forces that mitigate individual agent biases.

Contradiction Detection: Council deliberation naturally surfaces contradictions through structured debate. The orchestrator tracks inter-agent disagreements as inputs to the three-layer contradiction detection system (APIOSS-RES-002).

Domain Expertise: Each agent’s knowledge context is a subset of the knowledge graph (APIOSS-RES-003), enabling domain-grounded reasoning without

requiring all agents to process the full knowledge base.

Local-First Operation: All deliberation occurs locally through llama.cpp inference, requiring no network connectivity. This is critical for sovereign deployments in air-gapped environments (STIG, FedRAMP IL5).

6. Future Directions

6.1 Adaptive Agent Populations

Current MADA implementation uses a fixed set of three agents. Future work will explore dynamic agent populations where agents are instantiated based on decision type, complexity, and regulatory domain. Lertvittayakumjorn et al. [61] demonstrated that task-specific agent selection improves multi-agent system performance by 15-22%.

6.2 Dynamic Persona Generation

Personas are currently hand-crafted by system administrators. We plan to implement persona generation using Constitutional AI principles [42] with demographic distribution auditing. This would allow organizations to specify diversity requirements (e.g., “the council must include at least one non-majority perspective” or “the council must span at least three experience levels”) and have personas automatically generated to satisfy those constraints.

6.3 Formal Verifiability

The deliberation trajectory recorded in the AIOSS audit ledger enables post-hoc verification but not formal guarantees. Future work will explore probabilistic verification of council decisions using techniques from algorithmic game theory [62] and mechanism design [63]. Hong and Page’s diversity prediction theorem [21] provides a mathematical framework for bounding the worst-case performance of diverse agent councils.

6.4 Cross-Council Federation

In multi-tenant deployments with P2P federation (APIOSS-RES-006), councils from different organizational units could deliberate jointly on shared decisions while maintaining data sovereignty. CRDT-based consensus mechanisms [64] would enable asynchronous deliberation across network partitions.

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